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Early Autism Spectrum Disorder Screening In Toddlers: A Comprehensive Stacked Machine Learning Approach

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Abstract: In this paper, we have introduced a study that addresses the critical need for early detection of Autism Spectrum Disorder (ASD) in toddlers. ASD is characterized within the context of its profound impact on early childhood development, emphasizing the urgency of identifying it as early as possible. To achieve this, the study employs a diverse set of base models, including Logistic Regression, KNN, Decision Trees (DT), Support Vector Machines (SVM), and Neural Networks (NN), among others, as part of its methodology. One key aspect of the methodology is the meticulous execution of feature selection using these models. The focus is on identifying the top four features that are most indicative of ASD for subsequent training. By leveraging various machine learning algorithms, the study aims to develop accurate predictive models for early ASD detection, and a stacking technique is systematically applied, combining the strengths of different classifiers to further enhance performance. The most significant finding of the study is the exceptional accuracy rate of 99.148% achieved by the proposed approach. This high accuracy rate underscores the efficacy of the methodology in early ASD detection. By accurately identifying ASD in toddlers at an early stage, the study demonstrates the potential for timely intervention and support for affected children, ultimately improving their long-term outcomes and quality of life.

Keywords: Machine learning, Preference algorithm, Stacking, Feature selection, Classification, Confusion Matrix.

1. Introduction

Autism spectrum disorder (ASD)[1][2], also known simply as autism, is a complex condition that affects how people behave and communicate. It often involves repeating the same actions and challenges in social interactions [3], including online communication.In humans, it manifests in the first three years of life. A number of symptoms, including difficulties with communication and social contact, narrowed interests, and repetitive conduct, are what essentially define it. People with ASD have trouble comprehending the thoughts and feelings of others. Detecting autism early in life can have a significant impact, as early intervention and therapy can lead to improvements in communication skills and overall development. Symptoms typically begin to manifest between the ages of 12 to 18 months, making early detection [4] crucial for effective intervention.Diagnosing Autism Spectrum Disorder (ASD) poses a distinct challenge due to the absence of conventional medical diagnostics, like blood tests, to pinpoint the condition. Physicians typically use observational and psychological procedures for identifying ASD in their patients by looking into numerous aspects of their everyday lives, as shown in Figure 1. The research improved the identification of Autism by identifying the most important characteristics through the use of sophisticated machine-learning algorithms for feature selection. Using seven classifiers and merging the best five models, it used a stacking strategy to increase prediction accuracy overall. Through the combination of many classifiers' strengths, this strategy ensures more accurate and dependable findings for early Autism identification.

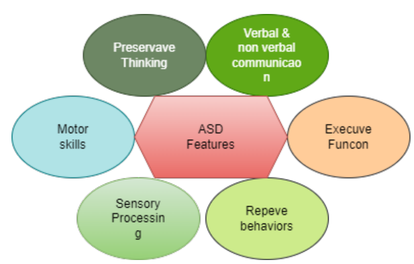

Figure 1. Features noted with ASD diagnosis

Our goal is to identify signs of autism at an early age to facilitate timely intervention and prevent the potential worsening of symptoms. Early detection not only improves outcomes for affected individuals but also helps reduce

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the long-term financial burden associated with later-stage intervention, such as the development of social skills and other necessary supports.

The World Health Organization (WHO) [5]estimates that one in every 160 children globally demonstrates characteristics of ASD, underscoring the issue's importance on a global scale.However, despite the growing prevalence of ASD, there remains a shortage of trained professionals to provide timely diagnosis and intervention. ASD diagnosis often relies on observing toddler behavior[6][7] and listening to parental concerns, making it a challenging task for healthcare providers.

Therefore, the objective of our work is to develop methods for early detection of ASD symptoms within the shortest possible timeframe, while also leveraging comprehensive datasets for enhancing the accuracy of existing research. By maximizing the use of available data and employing advanced analytical techniques, we aim to contribute to the early identification and intervention of autism spectrum disorder in toddlers, ultimately improving outcomes and quality of life for affected individuals and their families. Originally coined by Swiss psychiatrist Eugen Bleuler in 1908, the term "autism" was later refined by Leo Kanner in 1943 to describe social isolation and language difficulties in children. Hans Asperger identified a subgroup of children with similar traits but without significant language impairments, leading to the recognition of Asperger Syndrome.

In 1994 APA[8] published the DSM-IV[8]. In addition to other psychiatric diseases, this manual offers standardized criteria for the diagnosis and categorization of mental disorders. It also classifies a number of Pervasive Developmental diseases (PDDs)[8][9], but the DSM-V [8]introduced the broader category of Autism Spectrum Disorder to encompass the diverse range of symptoms seen across different disorders. Early diagnosis is essential and can be achieved through standardized diagnostic tools and collaboration among healthcare professionals.

In summary, diagnosing ASD [10] involves a comprehensive assessment that combines standardized assessments with clinical judgment to ensure accurate diagnosis and appropriate interventions. Disorder of Autism poses a significant challenge in the domain of child healthcare, impacting neurological development and impeding social interactions. The precise and timely ASD identification is crucial for timely interventions that can positively shape developmental trajectories, particularly in toddlers[11]. Addressing this issue is imperative, given the potential benefits of precise detection at an early stage. The motivation behind this research is rooted in recognizing the profound impact that early and accurate detection can have on guiding tailored interventions and providing essential support for affected individuals in the pediatric population.

Our approach follows a comprehensive methodology, beginning with feature selection. Initial models are tested on each feature individually, followed by evaluation on the top four features of the dataset. Subsequently, models are ranked based on accuracy metrics. For classification, we adopt a stacking technique, integrating the top five ML models[12] utilizing diverse classifiers including as LR, Random Forest, KNN Classifier, XGBoost, MLP Classifier, Catboost, and LightGBM.In particular, the approach we recommend achieves impressive results with an accuracy of 99.148%

The unique contribution of this paper lies in the application of machine learning principles to enhance predictive accuracy in Autism detection. Employing stacking methods with a variety of classifiers to refine accuracy metrics, our study aims to revolutionize predictive strategies, promising more effective and timely interventions in Autism Spectrum Disorder at an early age.

Contribution

1) **Intricate Feature Selection:**Employed machine learning models for detailed feature selection, ensuring the identification of crucial features.
   - **Detailed Feature Selection:** We applied advanced machine learning models to carefully select features. This process involves identifying which attributes or data points are most important for detecting Autism.
   - **Crucial Features Identified:** By focusing on the most relevant features, we ensure that our predictive models are more accurate and reliable, making it easier to detect Autism early on.
2) **Stacking with seven Classifiers:** Implemented a stacking technique using the best five models and seven different classifiers to enhance overall predictive accuracy.
   - **Stacking Technique:** We used a method called stacking, which involves combining multiple classifiers (or models) to improve overall prediction performance.
   - **Seven Different Classifiers:** We tested and integrated seven different classifiers, each contributing its strengths to the overall model.
   - **Optimal Model Selection:** From these, we selected the best five models to create an ensemble. This approach leverages the unique advantages of each model, enhancing the overall accuracy and robustness of our predictions.

2. Related works

In recent times, there have been noteworthy developments in the fields of autism early prediction and machine learning models[11].Shirajul Islam et al.[13].In order to accurately detect ASD at an early age, the paper uses machine learning to estimate the disorder and develop an online application.With machine learning, the study seeks to estimate ASD at a young age.obtaining information from the surveillance side Increasing the accuracy of early ASD estimation is the goal of this study.Maximum accuracy and speed are demonstrated by the KNN and Random Forest algorithms.Utilizing supervised learning techniques,particularly Random Forest and KNN,In terms of diagnosis speed and accuracy,KNN and Random Forest algorithms perform best.

Achenie et al.[14].have discussed how to screen toddlers for autism using a machine learning technique called a feedforward neural network (fNN)[15].A comparison of the fNN method's performance with the M-CHAT-R [14]suggests that the ML technique can produce valid screening results with fewer items.Feedforward neural networks (fNNs) are used in machine learning (ML) techniques for toddler autism screening.With 18 items, the machine learning approach produced a 99.72% accurate categorization rate.The feedforward neural network (fNN) method of machine learning was employed in the study.With 18 items,the machine learning approach produced a 99.72% accurate categorization rate.Even with fewer items than the M-CHAT-R,the ML approach attained accuracy that was comparable.

Taraque,Md Fakrul and Hasan,S.M.Mahedy and Jannat et al.[16]aim to improve the early detection of autism spectrum disorder(ASD)using machine learning(ML).Researchers analyzed three ASD datasets from UCI,comparing six traditional classifiers and ensemble methods. They found that Decision Tree with boosting performed best for adolescents,Logistic Regression for children, and Support Vector Machine with boosting for adults,enhancing prediction accuracy and reducing bias.

M. Ponni Bala et al.[17]introduced a variety of feature selection methods and classifiers.The study suggests a machine learning model that may accurately and early identify ASD.An preliminary ASD detection is proposed using a ML algorithm.Communication and social skills are impaired in people with ASD,a neurodevelopmental disease.Techniques for selecting features When it came to different age groups,support vector machines (SVM)outperformed other classifiers.Other classifiers did not perform in addition to Support Vector Machines. In order to provide appropriate therapy and enhance results,early identification of ASD is essential.Classification formulas Interpreting the data was done using the Shapley Additive Explanations (SHAP) approach.

S. M.Mahedy Hasan,Md Palash Uddin et al.[18]has focused on strategy for early diagnosis of illnesses associated with autism spectrum.A proposed ML system for the early identification of diseases associated with autism spectrum(ASD).A plan for recognizing autism spectrum illnesses in their early stages is suggested.4 distinct approaches to feature scaling (FS):Max Abs Scaler(MAS)AB,QT, PT, Normalizer,and Normalizer the Toddlers dataset's predicted ASD with the best accuracy of 99.25%. Analyzing feature scaling tactics and machine learning methods for categorizationFramework assesses feature scaling strategies and machine learning approaches on ASD datasets.Assessment of diverse Machine Learning methodologies for the identification of ASD.The eight machine learning methods are:Ada Boost (AB),GNB,DT,RF,KNN,LR,SVM and Linear Discriminant Analysis.

Shrivastava,Trapti and Singh,Vrijendra [19]use machine learning to distinguish between people with autism spectrum disorder(ASD)and normally developing(TD)people in a range of age groups. In comparison to conventional diagnostic procedures, the study offers a more accurate and efficient way for early ASD detection using models like Random Forest, which obtained 100% accuracy.This method works better than sophisticated models like CNN and DNN, which makes it a useful tool for clinical diagnosis in real time.

Kavitha,V.and Siva,R [20]applied machine learning to enhance the early detection of autism spectrum disorder (ASD).It presents a detection method based on the particle swarm optimization algorithm(PSO-CNN)in conjunction with a convolutional neural network. In order to compare PSO-CNN with more conventional techniques like SVM, Naive-Bayes, and Logistic Regression, the study examines four datasets:toddlers, adults, children, and adolescents. The PSO-CNN model's high accuracy (98.1%) in predicting ASD is demonstrated by the results, highlighting its usefulness and efficiency in addressing missing data and enabling early diagnosis.

Analyzing feature scaling tactics and machine learning methods for categorizationFramework assesses feature scaling strategies and machine learning approaches on ASD datasets.Assessment of diverse Machine Learning methodologies for the identification of ASD.The eight machine learning methods are: Ada Boost(AB),GNB,DT,RF,KNN,LR,SVM and Linear Discriminant Analysis.

Ashima Sindhu Mohanty et al.[21] proposes a ML methodology for classifying toddlers with ASD that makes use of dimension reduction, preprocessing techniques, and different classification models.The proposed work focuses on the classification of ASD toddlers using machine learning.The study uses ML to classify toddlers who have ASD.Preprocessing:converting category variables into numerical values and standardizing numerical properties produced incredibly accurate categorization results.Preprocessing, classification, and dimension reduction are examples of analysis steps.Preprocessing, classification,and dimension reduction are examples of analysis steps.Sorting:Using k-fold cross validation(k=10)for ML classification models, the training parameter e outperformed other pioneering techniques concerning performance.

Ahmed Shihab Albahri et al. [22]emphasized on the field of ASD inspection enhancement,which combines con-

TABLE I. Features and Descriptions

Feature	Type	Description
A1	(0, 1) Binary	Response to Question 1: The assigned code denoting the screening method utilized for the question.
A2	(0, 1) Binary	Response to Question 2: The code representing the question's answer in accordance with the screening method.
A3	(0, 1) Binary	Response to Question 3: The answer code linked to the screening method used for the question.
A4	(0, 1) Binary	Response to Question 4: The code associated with the question's answer as per the employee screening approach.
A5	(0, 1) Binary	Response to Question 5: The answer code corresponding to the screening method applied to the question.
A6	(0, 1) Binary	Response to Question 6: The code indicative of the question's response within the screening method.
A7	(0, 1) Binary	Response to Question 7: The assigned code reflects the screening method utilized for the question.
A8	(0, 1) Binary	Response to Question 8: The answer code correlated with the screening method employed for the question.
A9	(0, 1) Binary	Response to Question 9: The code denoting the question's response within the screening method.
A10	(0, 1) Binary	Response to Question 10: Age categorization for toddlers (months) - Less than or equal to 3: no ASD traits; more than 3: ASD traits.
Age	Integer	Age: Gender specification - Male or Female.
Score by Q-chat-10	Integer	Compilation of common ethnicities in textual format.
Sex	Character	Details on whether jaundice was present at birth in the case.
Ethnicity	String	Inquiry about anybody living in the same household having a Pervasive Developmental Disorder (PDD).
Born with jaundice	Boolean (yes or no)	Source of information: Parent, self, caregiver, medical staff, clinician, etc.
Family member with ASD history	Boolean (yes or no)	Interactive text box for user input.
Who is completing the test	String	Classification of ASD traits or No ASD traits, automatically assigned by the ASDTests app: Yes/No.
Why are you taking the screening	String	The response code indicating the question's screening method applied.
Class variable	String	The assigned code denoting the screening method utilized for the question.

ventional feature selection methods with machine learning approaches.ASD is a broad term that includes a range of neurodevelopmental disorders that have an important bearing on communication and social skills.The literature review emphasizes how important machine learning techniques are to improving ASD diagnostic procedures. Traditional feature selection techniques that concentrate on relevant features are used in the study, along with strategies like model-based imputation to handle missing data.The Gradient Boosting (GB) model, which achieves extraordinary accuracy, recall, and precision rates of 87%, 87%, and 86%, respectively, stands out for its exceptional performance. The effectiveness of this suggested methodology in detecting ASD is confirmed by its superior performance on several crucial criteria.

As per Ayşe Demirhan[23],the machine learning system explored in the article, achieved an 86.5% agreement with ASD statuses reported by clinicians. Surveillance systems have difficulties due to the social communication deficiencies associated with ASD.The method demonstrated a sensitivity of 84.0% and a positive predictive value of 89.4% utilizing random forests and variable significance ratings.

Aythem Khairi Kareem[24]proposes utilizing a 1D CNN for ASD detection. Here, 1D CNNs outperform traditional machine learning algorithms in ASD classifica-

TABLE II. Description of Child's Behavior

Item	Description
A1	When you call their name, does your youngster make eye contact in return?
A2	How comfortable is it for your youngster to look you in the eye?
A3	When anything, like a toy that's out of reach, is desired by your kid, does he or she point?
A4	Is your youngster indicate that they both find something interesting, like a fascinating sight?
A5	Does the kid engage in pretend play, like caring for playthings or talking on a dummy phone?
A6	Does the youngster follow your gaze to see where you are looking?
A7	Does your child exhibit any outward signals of wanting to console someone who appears distressed, such as petting their hair or offering them a hug?
A8	What would you say about your child's initial verbal exchanges?
A9	Is your youngster wave you off or make other basic gestures?
A10	Does your youngster sometimes look at nothing for no apparent reason?

tion,highlighting their potential for improving accuracy. The study underscores the inconsistency of traditional methods in ASD classification. Notably,1D CNNs demonstrate significant accuracy enhancements,achieving 99.45%, 98.66%,and 90% accuracy in screening adults, children, and adolescents respectively,surpassing traditional algorithms

Goel,Lipikaand Gupta,Sonam and Gupta, Avdhesh and Rajan et al.[25]use structural MRI data for early ASD detection, the research presents the Autism Spectrum Disorder-based Attention Graph Neural Network with Crossover Boosted Meerkat Optimization(ASD-AttGCBMO).The approach tackles issues such as domain shift, imbalanced classes,and overfitting.In order to improve model performance,it preprocesses MRI images, extracts features using surface-based analysis and voxel-based morphometry, and uses Adam and SGD optimizers. The ASD-AttGCBMO model has an AUC/ROC of 0.989,computes in 3.05 seconds,and achieves good accuracy (98.8%),precision (99%),recall (98.5%), and F1-score(98.2%).It performs better in ASD categorization than current cutting-edge techniques.

Nie, Wei and Zhou, Bingrui and Wang et al. [26]enhance the evaluation of autistic sociability in kids with ASD,the study presents the Computational Interpersonal Communication Model(CICM). With CICM,evaluation is scenario-independent and based on stochastic processes and psychological theory,unlike traditional subjective approaches. Applying the CICM indications to a response-to-name test with 48 children (30 ASD,18 usually developing),the test findings were effective and comprehensible,exhibiting good consistency with expert evaluations(98.44%) and ASD diagnosis(83.33%).

3. Materials and methodology

A. Dataset

In response to the scarcity of clinical autism datasets,as mentioned in TABLE I particularly those tailored for toddler screening[27],this proposal introduces a new dataset aimed at enhancing the classification of ASD cases. The used dataset includes 1054 instances and 18 attributes as outlined in Figure 2,featuring ten behavioral aspects as shown in TABLE II(Q-Chat-10) [28][29] alongside other influential characteristics for effective ASD detection and Figure 3 explains about number of autism cases before and after sampling.The data encompasses predictive and descriptive elements with nominal/categorical, binary, and continuous values. Classified within the medical, health, and social science domains, the non-matrix formatted dataset lacks missing values. Notably, ASD traits are determined based on a scoring system applied to the Q-Chat-10 responses, offering potential contributions to ASD research and classification.Figure 4shows the correlation between the features.

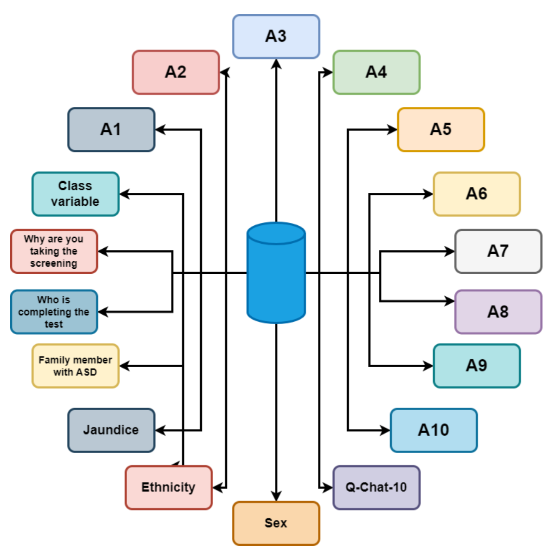

Figure 2. Dataset

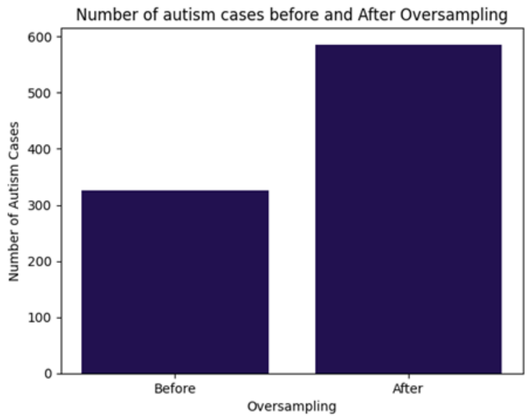

Figure 3. Before and after sampling

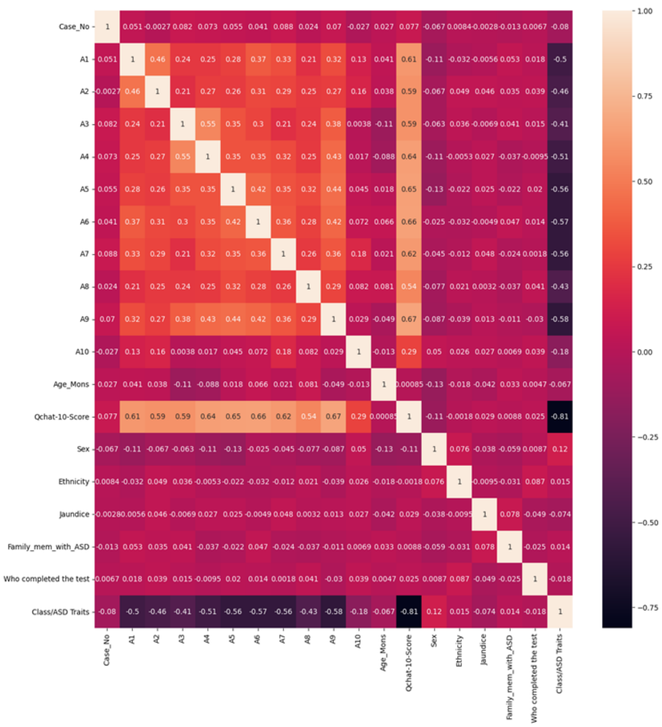

Figure 4. Correlation between features

B. feature selection

Seven models were trained using various datasets, each comprising features such as A1,A2,A3,A4,A5,A6,A7,A8,A9,A10,Age,Q-chat-10 Score,Sex,Ethnicity,Jaundice at Birth, Family History of ASD,Test Completer,Screening Motive, and the target variable - Autism classification. The process of extraction features meticulously separated each feature alongside the autism column,resulting in eighteen distinct datasets.Subsequently, these datasets were utilized to train seven models independently,and the resulting accuracies were methodically documented,as outlined in TABLE III.

The TABLE IV presents the performance metrics of various machine learning models trained on datasets with different numbers of features.Each row corresponds to a specific machine learning model,while the columns represent the accuracy achieved by the models when trained on datasets containing a varying number of features.

Upon examining the table,it becomes apparent that certain machine learning models exhibit improved accuracy when trained on datasets with a specific number of features.For instance,the ”K-Nearest Neighbors” model achieves its highest accuracy of 78.977% when trained on datasets with the top 6 features, whereas the ”Ada Boost” model performs optimally with an accuracy of 72.159% when trained on datasets containing the top 6 features.

Similarly,the ”SVM-L” model achieves its highest accuracy of 58.523% when trained on datasets with the top 6 features, whereas the ”Naive Bayes” model performs best with an accuracy of 59.102% when trained on datasets containing the top 5 features.

Interestingly,the ”Neural Network” model exhibits its highest accuracy of 59.409% when trained on datasets with the top 4 features, indicating that this model performs well with a relatively lower number of features.

Overall,the table provides valuable insights into the performance of various machine learning models concerning the number of features present in the dataset, enabling researchers and practitioners to make informed decisions when selecting models for specific applications based on the dataset’s characteristics.

After thorough analysis,our study has identified the top-performing features selected by various classifiers. Specifically,we have curated a set of features based on the results obtained from different classifiers.Our selection comprises the top 4 features from Logistic Regression and Neural Network models,the top 5 features from Naive Bayes and Multinomial Naive Bayes (MNB), and the top 6 features from K-Nearest Neighbors, Support Vector Machine with Linear kernel (SVM-L),and Ada Boost classifiers.All model accuracy comparisons with different numbers of features have been displayed in figure 5and TABLE Vshows the accuracy of different models with preferred features.This meticulous curation process ensures that only the most discriminative and informative features are retained for further analysis and model optimization.

C. Classification

A stacking approach for classification has been employed,selecting the top-performing five models based on accuracy metrics evaluated on the top six features. The process of feature selection aimed for identification of the Most fascinating attributes for enhancing classification performance.The chosen models, including KNN,NB, AdaBoost, Multilayer Perceptron (NN),and Support Vector Machine (Linear Kernel),were individually trained on the

TABLE III. Accuracy of Different Models

Col	LR	KNN	SVM(L)	NN	NB	Ada	MNB
1	81.82	86.36	81.82	81.82	81.82	82.39	81.82
2	73.58	81.82	73.58	73.58	73.58	75.57	73.58
3	53.98	76.99	59.38	50.28	59.09	66.48	53.13
4	71.02	82.95	71.02	71.02	71.02	75.57	71.02
5	76.99	84.38	76.99	76.99	76.99	79.26	76.99
6	82.67	87.50	82.67	82.67	82.67	85.23	82.67
7	82.10	86.93	82.10	82.10	82.10	82.39	82.10
8	79.26	86.36	79.26	79.26	79.26	80.68	79.26
9	77.84	85.51	77.84	77.84	77.84	78.98	77.84
10	82.96	87.22	82.96	82.96	82.96	85.51	82.96
11	58.24	76.99	54.26	60.23	61.93	70.17	53.69
12	58.24	76.99	54.26	60.23	61.93	70.17	53.69
13	99.89	99.97	99.12	99.47	99.70	99.67	99.87
14	55.11	82.10	55.11	66.19	56.25	67.61	56.25
15	51.14	77.84	52.56	63.64	52.27	67.33	47.73
16	52.56	79.55	52.56	55.40	51.99	62.50	51.71
17	57.39	78.98	57.39	53.69	53.98	67.90	50.57
18	51.71	79.55	51.42	54.55	47.16	59.94	47.16

TABLE IV. Model Accuracy with Different Feature Sets

Model Name	Accuracy (Top 4 Features)%	Accuracy (Top 5 Features)%	Accuracy (Top 6 Features)%
Logistic Regression	**57.409**	57.102	53.102
K-Nearest Neighbors	77.557	76.42	**78.977**
SVM-L	45.739	45.17	**58.523**
Neural Network	**59.409**	56.818	53.091
Naive Bayes	58.523	**59.102**	58.807
Ada Boost	68.75	68.182	**72.159**
MNB	55.966	**57.409**	53.386

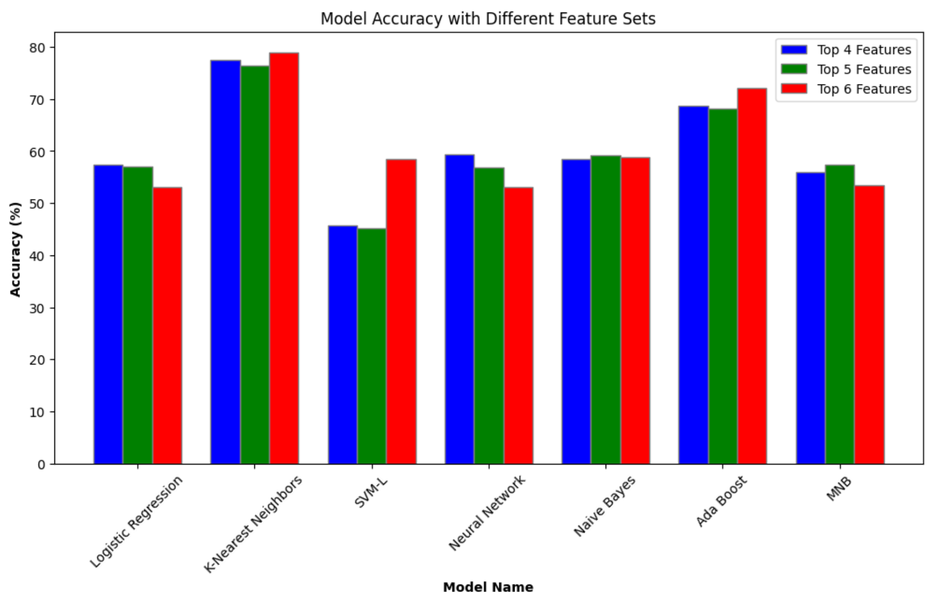

Figure 5. All model Accuracy comparison with different number of features

dataset using the top six features. Subsequently,a stacking classifier was implemented, incorporating these diverse base models.Stacking,as a model ensemble technique, aimed to leverage the strengths of individual models and enhance overall predictive accuracy.Standard classification criteria,such as accuracy, precision,recall,and F1-score,were used to assess the stacking model's performance. This comprehensive approach contributes to the investigation of optimal model ensembles for classification tasks, providing insights into the effectiveness of stacking diverse classifiers in improving classification accuracy on the selected feature subset.

Stacking

The stacking of classifiers utilized in this study encompassed a diverse set of models,each contributing unique strengths to the overall predictive framework.The Stacking approach incorporated individual models such as the KNN classifier, Gaussian NB,AdaBoost,SVM,and Multilayer Perceptron(NN),showcasing a variety of algorithmic techniques.These models were judiciously chosen based on their demonstrated performance in capturing patterns within the dataset.

4. Results & discussion

In TABLE VII,We thoroughly assessed our stacking approach with different classifiers,employing a comprehensive set of performance metrics. We computed accuracies, precision, recall, and F1-score to gauge the model's predictive efficacy relative to the ground truth labels within the dataset.A balanced indicator of recall and precision is the F1-score, while accuracy indicates the overall accuracy of predictions.The percentage of true positive forecasts to all positive predictions is quantified by precision.Recall evaluates how well the model incorporates all actual positive cases. .

A. evaluation matrix

Each cell in the multi-class confusion matrix displays the number of examples that correspond to the specified classes and the model predictions for each of those classes.This matrix serves as a visual aid, elucidating the model's classification accuracy and potential misclassifications across various class categories.

Based on TABLE VI the following metrics are obtained for every class $c \in C$ based on these confusion matrices:

- **Recall (recc)**: $\frac{TPc}{TPc+FNc}$
- **Precision (precc)**: $\frac{TPc}{TPc+FPc}$
- **Dice Coefficient (Dicec)**: $\frac{2 \times precc \times recc}{precc+recc}$, comparable to the Formula One Score. These measures range of values is $[0, 1]$.

B. Performance of classifier

The stacking classifiers included Stacking with LightGBM,CatBoost,KNN,RF,MLP, Logistic Regression, and Decision Tree. Each stacking model integrated a combination of base classifiers such as KNN,Gaussian NB,AdaBoost,SVM,and Multilayer Perceptron.The stacking ensemble methodology aimed to capitalize on the diverse capabilities of these individual classifiers,effectively leveraging their distinct learning patterns and features.The stacking process involved aggregating predictions from multiple base classifiers through a meta-classifier, resulting in comprehensive and nuanced predictions. The use of multiple stacking models reflected a strategic approach to ensemble learning, emphasizing the adaptability and enhanced predictive performance achieved by amalgamating diverse classification algorithms.This comprehensive ensemble strategy contributed to a robust and versatile predictive framework. Visualizations of the accuracy,precision, F1 Scores,recall have been presented in Figures 7, 8,9, 10 and clear comparison has been put up in Figure 6.

After evaluating the performance metrics of various stacking classifiers for the top 5 models,it is evident that LightGBM stands out as the most promising model. With an impressive accuracy of 99.148% and a robust F1-Score of 99.071%, LightGBM excels in both precision and recall,demonstrating a superior balance in capturing decreasing false positives and false negatives while increasing genuine positive cases.The 98.765% precision underscores the model's ability to make correct positive predictions, while a recall of 99.379% highlights its effectiveness in capturing a substantial portion of actual positive instances. This exceptional performance positions LightGBM as the recommended choice for predictive modeling in this context,showcasing its capacity to deliver accurate and well-balanced predictions across diverse scenarios.

In TABLE VIII, the performance metrics of various machine learning classifiers,including Logistic Regression,Random Forest,KNN Classifier,MLP Classifier,Decision Tree,CatBoost, and LightGBM,are compared.Each classifier's accuracy,precision,recall,and F1-score are evaluated to assess their effectiveness in identifying ASD in toddlers.

Among the classifiers tested,the proposed method stands out significantly,achieving remarkable performance across all metrics. With an accuracy of 99.148% precision of 98.765%,recall of 99.379%,and F1-score of 99.071%,the proposed method demonstrates superior performance compared to other traditional machine learning models.This exceptional accuracy underscores the effectiveness of our methodology in early ASD detection, highlighting its potential for timely intervention and support for affected toddlers.

In contrast, while some traditional classifiers like LR,RF,KNN Classifier,and DT show moderate performance,with accuracies ranging from 56.453%to

TABLE V. Accuracy of Different Models with preferred Features

Model Name	Accuracy (%)
K-Nearest Neighbors	78.977
Ada Boost	72.159
Naive Bayes	59.091
Neural Network	58.807
Support Vector Machine (Linear Kernel)	58.523

TABLE VI. Confusion Matrix Terminology

Abbreviation	**Description**
TPc (True Positive)	Represents instances where the model correctly identifies a particular class (like ”core”).
FPc (False Positive)	Indicates cases where a class (like ”core”) that is absent from the real data is mistakenly predicted by the model.
FNc (False Negative)	Indicates instances where the model fails for the prediction of a class (e.g., ’core’) that does exist in actual data.
TNc (True Negative)	Refers to instances where the model accurately identifies the absence of a class (e.g., ’core’) that is indeed absent in the actual data.

TABLE VII. Experiment with different classifiers on our proposed method

Classifier	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
Logistic Regression	64.773	58.768	77.019	66.667
Random Forest	75.284	70.787	78.261	74.336
KNN Classifier	78.693	99.70	53.416	69.636
MLP classifier	71.09	99.87	11.594	20.779
Decision Tree	59.716	25	11.594	15.842
CatBoost	91.477	93.377	87.578	90.385
LightGBM	99.148	98.765	99.379	99.071

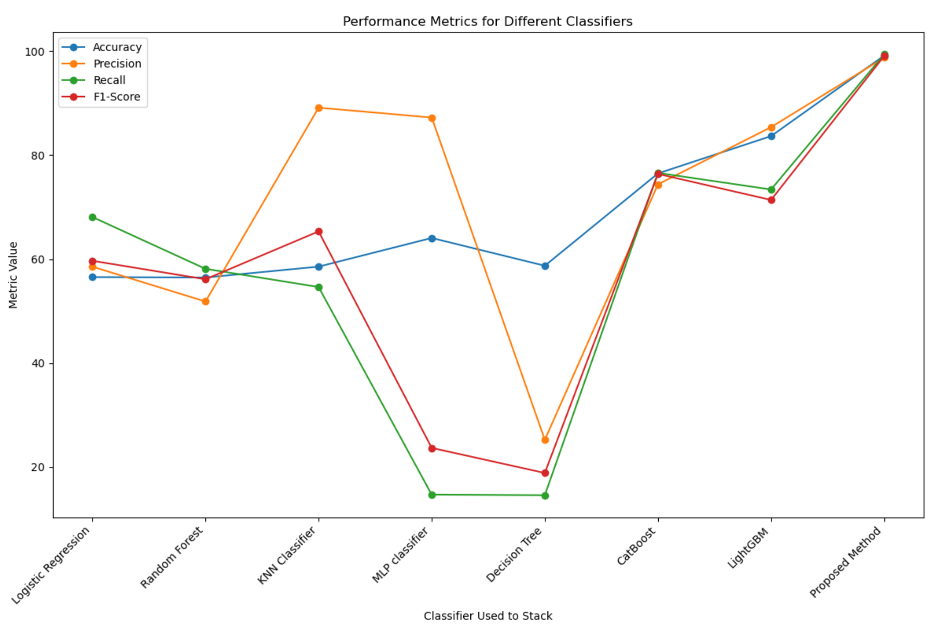

Figure 6. Comparison of all the metrics

TABLE VIII. Classifier Performance Metrics

Classifier	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Logistic Regression	56.53	58.538	68.092	59.671
Random Forest	56.452	51.832	58.125	56.113
KNN Classifier	58.543	89.132	54.623	65.326
MLP classifier	64.06	87.234	14.675	23.668
Decision Tree	58.716	25.214	14.564	18.842
CatBoost	76.477	74.377	76.578	76.385
LightGBM	83.657	85.377	73.388	71.375
Proposed Method	**99.148**	**98.765**	**99.379**	**99.071**

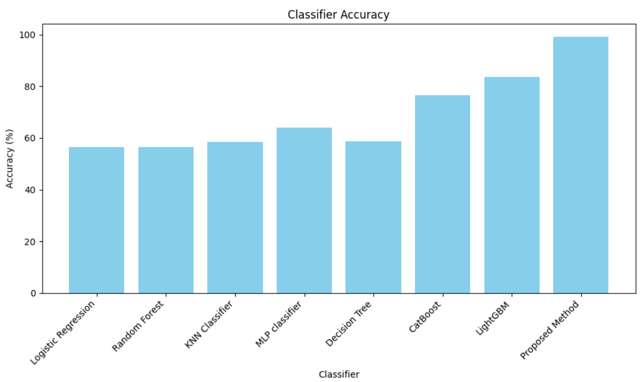

Figure 7. Accuracy comparison

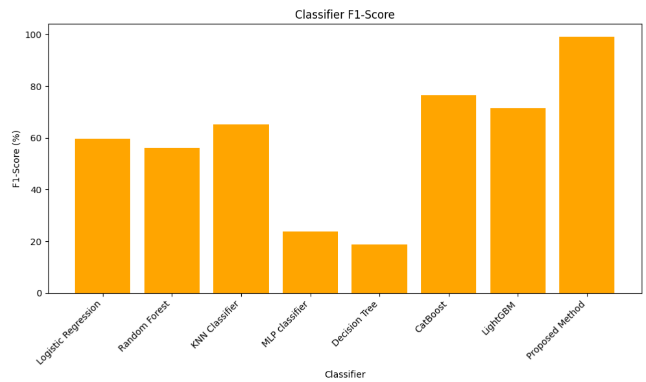

Figure 9. F1 Score comparison

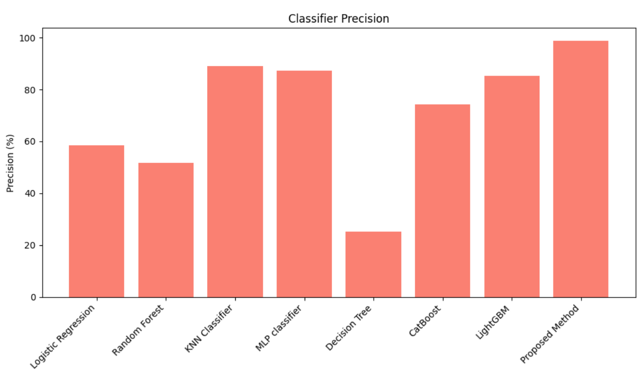

Figure 8. Precision comparison

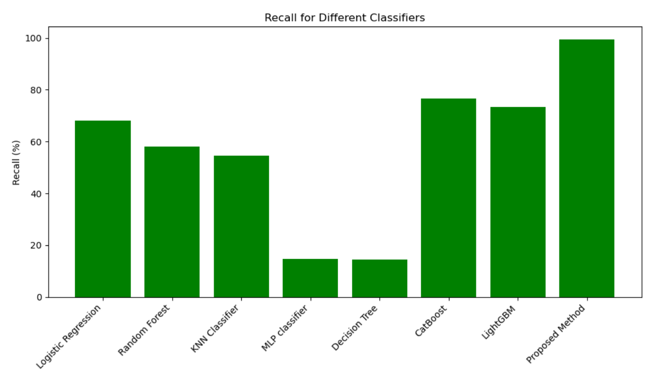

Figure 10. Recall comparison

58.716%,they fall short in terms of precision,recall,and F1-score.MLP Classifier exhibits relatively higher accuracy (64.060%),but its performance in terms of precision,recall,and F1-score is considerably lower compared to the proposed method.

CatBoost and LightGBM, on the other hand, demonstrate competitive performance,with accuracies of 76.477%and 83.657%, respectively.However,the proposed method surpasses both CatBoost and LightGBM in respect to the accuracy,precision, recall, and F1-score,highlighting its efficacy in early ASD detection.

Overall,the comparison illustrates the superior performance of our proposed method in accurately identifying ASD symptoms in toddlers,emphasizing its potential for revolutionizing early intervention strategies and improving outcomes for affected individuals and their families.

5. Conclusion and Future work

In conclusion, our research underscores the significance of early detection in ASD among toddlers and the potential transformative impact on their developmental trajectories.By employing a comprehensive methodology that integrates intricate feature selection,model stacking techniques,and rigorous evaluation metrics,we have demonstrated promising results in accurately identifying ASD symptoms at an early age.Our approach, characterized by the meticulous selection of top-performing models and the utilization of various classifiers,has yielded exceptional accuracy rates,Significantly,our proposed approach yields exceptional results of 99.148% accuracy. These outcomes underscore the efficacy of our methodology in the early detection of ASD,demonstrating the potential for timely interference and support for affected toddlers.These outcomes underscore the efficacy of our methodology in facilitating timely intervention and support for affected toddlers,ultimately improving their long-term outcomes and quality of life.

Looking ahead, future research endeavors in the field of early autism detection should focus on longitudinal studies to track developmental trajectories, integration of additional data sources for enhanced predictive accuracy,refinement of stacking techniques for optimization, validation of models in clinical settings, and the development of user-friendly tools for community-based screening.By continuing to advance our understanding and approach to early autism detection, we can further improve outcomes for individuals and families affected by ASD, ensuring that timely interventions are readily available to support their unique needs and challenges.

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